GENERAL ASSEMBLY

INTRO TO DATA SCIENCE

MAP-REDUCE

AGENDA

I. BIG DATA

II. PROGRAMMING MODEL

III. IMPLEMENTATION DETAILS

IV. WORD COUNT EXAMPLE

NEXT STEPS

I. BIG DATA

As you have probably heard, **big data** *is a hot topic these days.*

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But this is only half of the story...how would you do this?

One approach would be to get a huge supercomputer.

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But this has some obvious drawbacks:

- *expensive*
- *difficult to maintain*
- *scalability is bounded*

Instead of one huge machine, what if we got a bunch of regular (commodity) machines?

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This has obvious benefits!

- cheaper

- easier to maintain

- scalability is unbounded (just add more nodes to the cluster)

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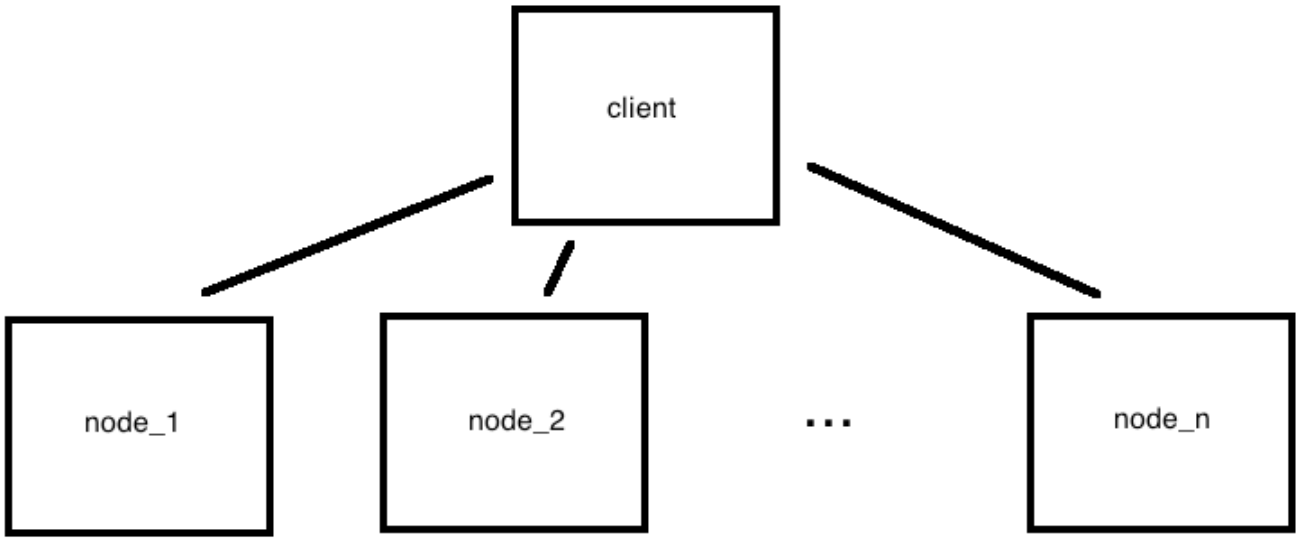
"Scale out vs scale up!"

We can visualize this horizontal cluster architecture as a single client-multiple server relationship



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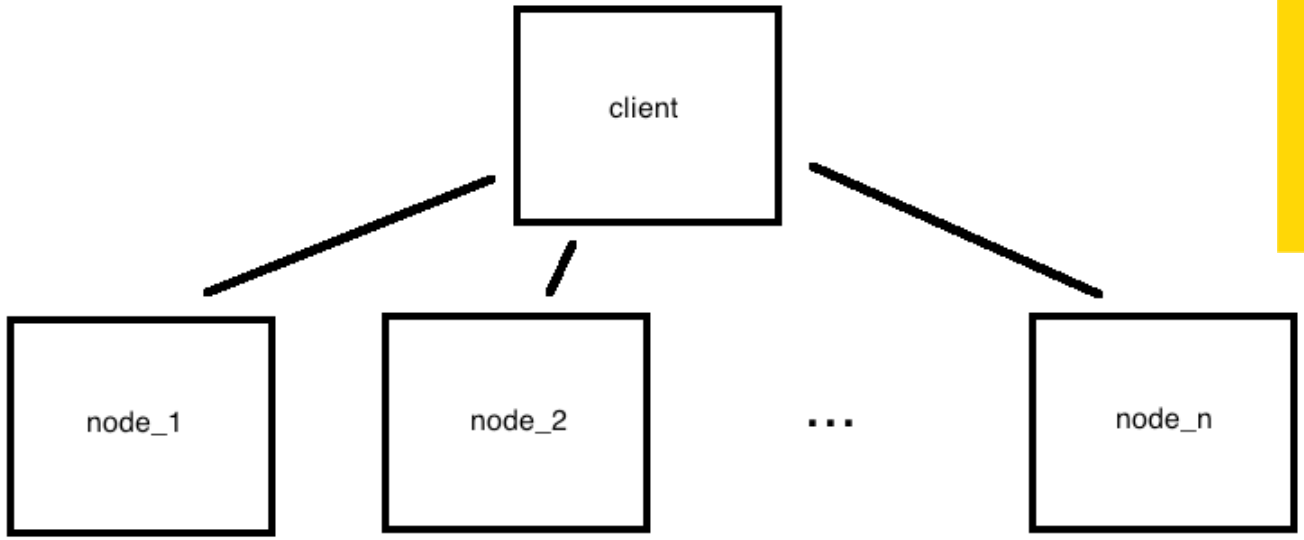

NOTE

A horizontally distributed system also has better *fault tolerance* than a single machine.

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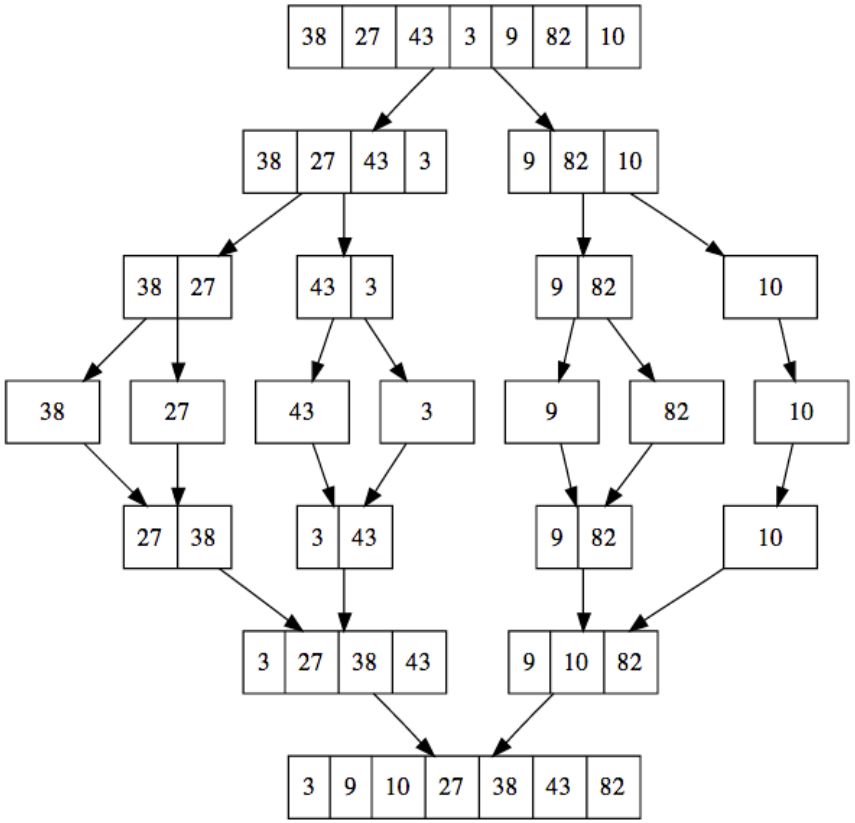
This is how recursive algorithms work, for example.

ASIDE: DIVIDE AND CONQUER ALGORITHMS

One famous example of divide and conquer is merge sort.



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(The similarity is approximate, because results are output in multiple sets, and data is not broken down to single-element subsets.)

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NOTE

Parallelizing an ML algorithm can be a non-trivial exercise!

II. PROGRAMMING MODEL

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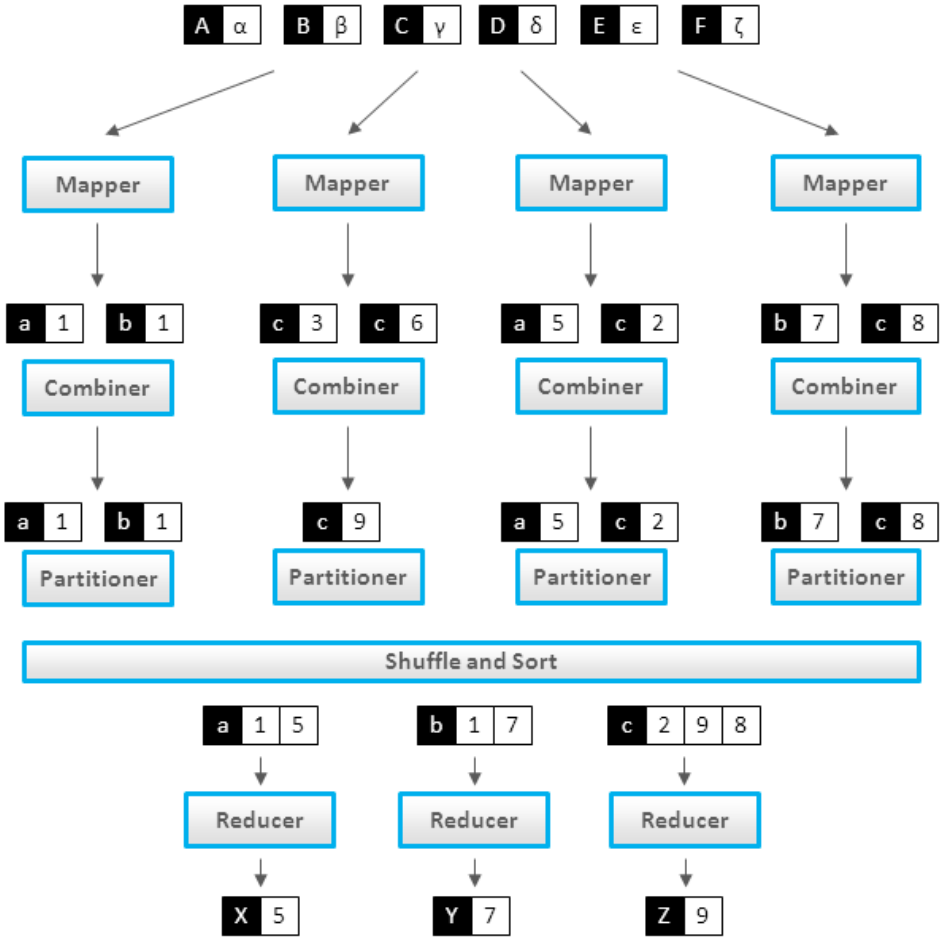
1) the **mapper** *phase*
1.5) shuffle/sort
2) the **reducer** *phase*


A α
B β
C γ
D δ
E ε
F ζ
Mapper
Mapper
Mapper
Mapper
a 1
b 1
c 3
c 6
a 5
c 2
b 7
c 8
Combiner
Combiner
Combiner
Combiner
a 1
b 1
c 9
a 5
c 2
b 7
c 8
Partitioner
Partitioner
Partitioner
Partitioner
Shuffle and Sort
a 1 5
b 1 7
c 2 9 8
Reducer
Reducer
Reducer
X 5
Y 7
Z 9

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The functional paradigm is good at describing how to solve a problem, but not very good at describing data manipulations (eg, relational joins).

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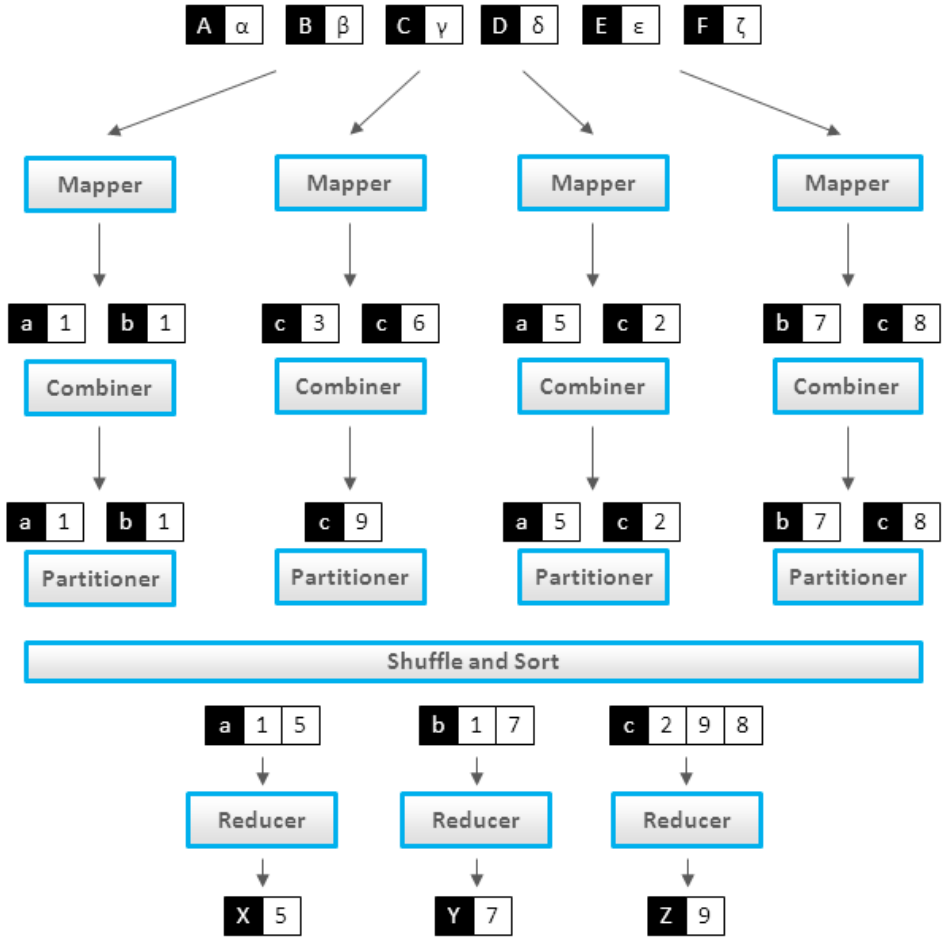
mappers – *filter & transform data*
combiners – *perform reducer operations on the mapper node (optional step, to reduce network traffic and disk I/O).*
partitioners – *shuffle/sort/redirect mapper output*
reducers – *aggregate results*


A α
B β
C γ
D δ
E ε
F ζ
Mapper
Mapper
Mapper
Mapper
a 1
b 1
c 3
c 6
a 5
c 2
b 7
c 8
Combiner
Combiner
Combiner
Combiner
a 1
b 1
c 9
a 5
c 2
b 7
c 8
Partitioner
Partitioner
Partitioner
Partitioner
Shuffle and Sort
a 1 5
b 1 7
c 2 9 8
Reducer
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Reducer
X 5
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Z 9

II. IMPLEMENTATION DETAILS

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- parallelization & distribution (eg, input splitting)

- partitioning (shuffle/sort/redirect)

- fault-tolerance (fact: tasks/nodes will fail!)

- I/O scheduling

- status and monitoring

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This (along with the functional semantics) allows you to focus on solving the problem instead of accounting & housekeeping details.

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Hadoop is written in Java, but the Hadoop Streaming utility allows client code to be supplied as executables (eg, written in any language).

Frequently when people say "map-reduce" they're referring to Hadoop, but there are some exceptions:

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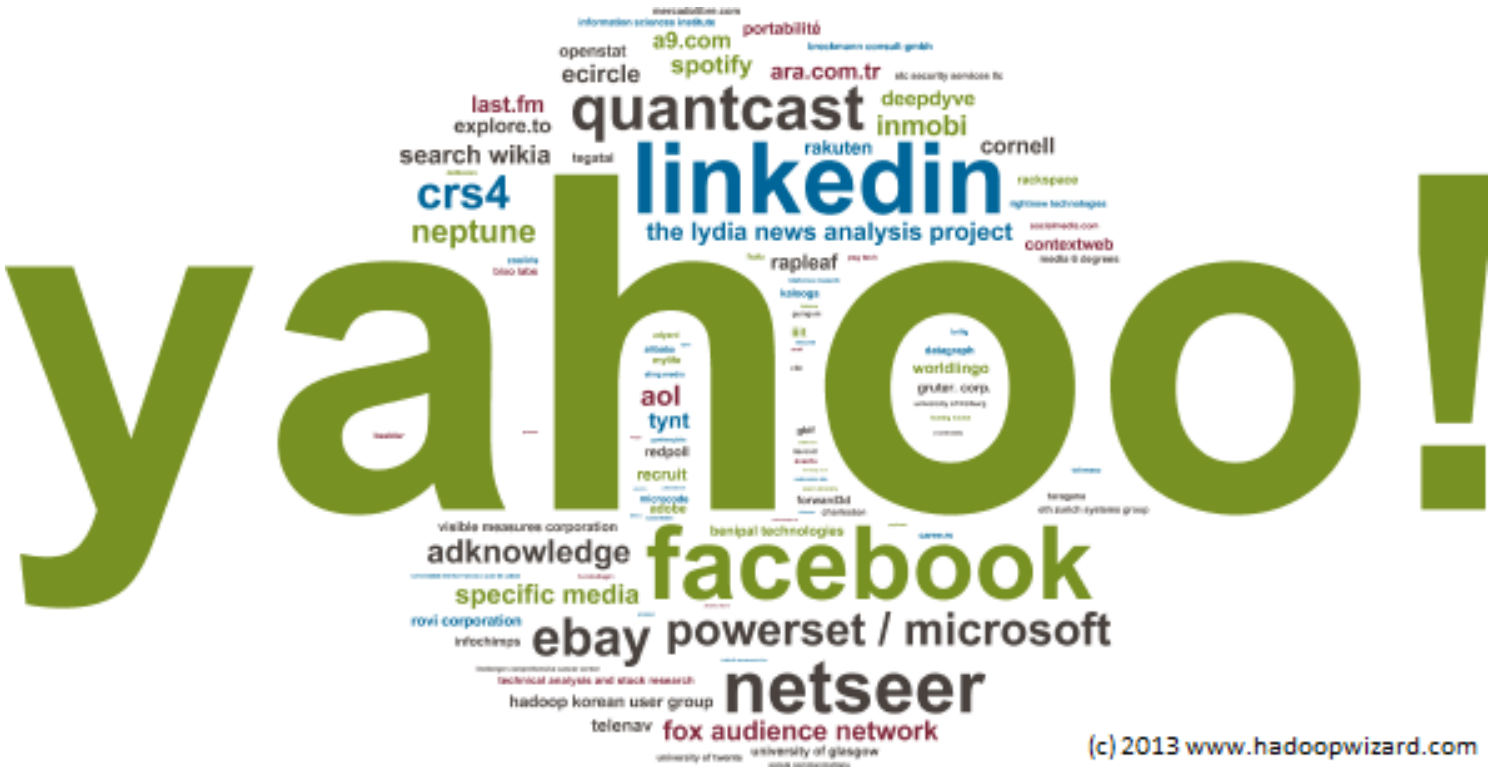
- many NoSQL databases support native map-reduce queries
- commercial distributions (Cloudera, MapR, etc)
- Google's internal implementation

That said, Hadoop has a large user base.



source: http://www.hadoopwizard.com/which-big-data-company-has-the-worlds-biggest-hadoop-cluster/

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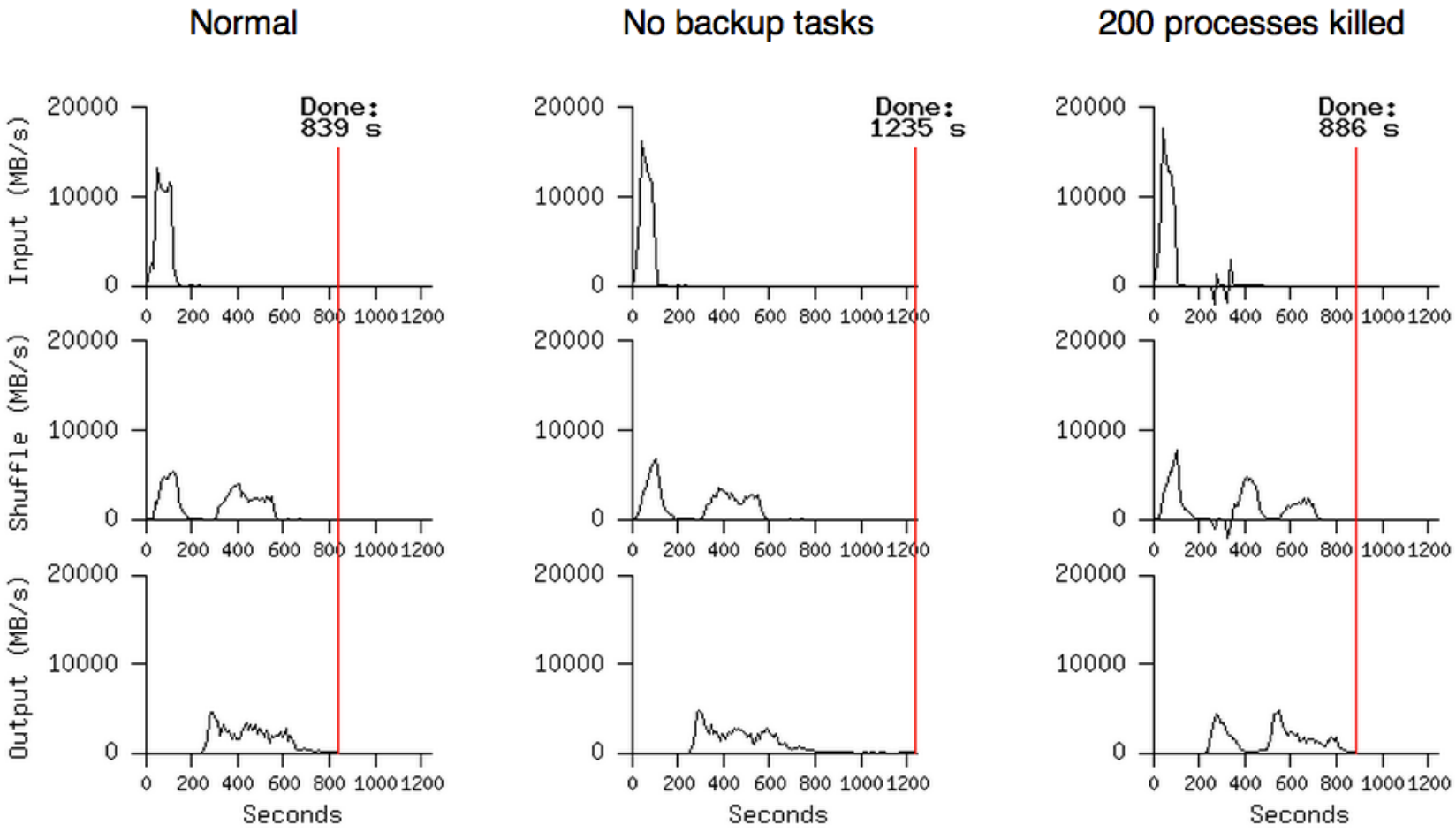
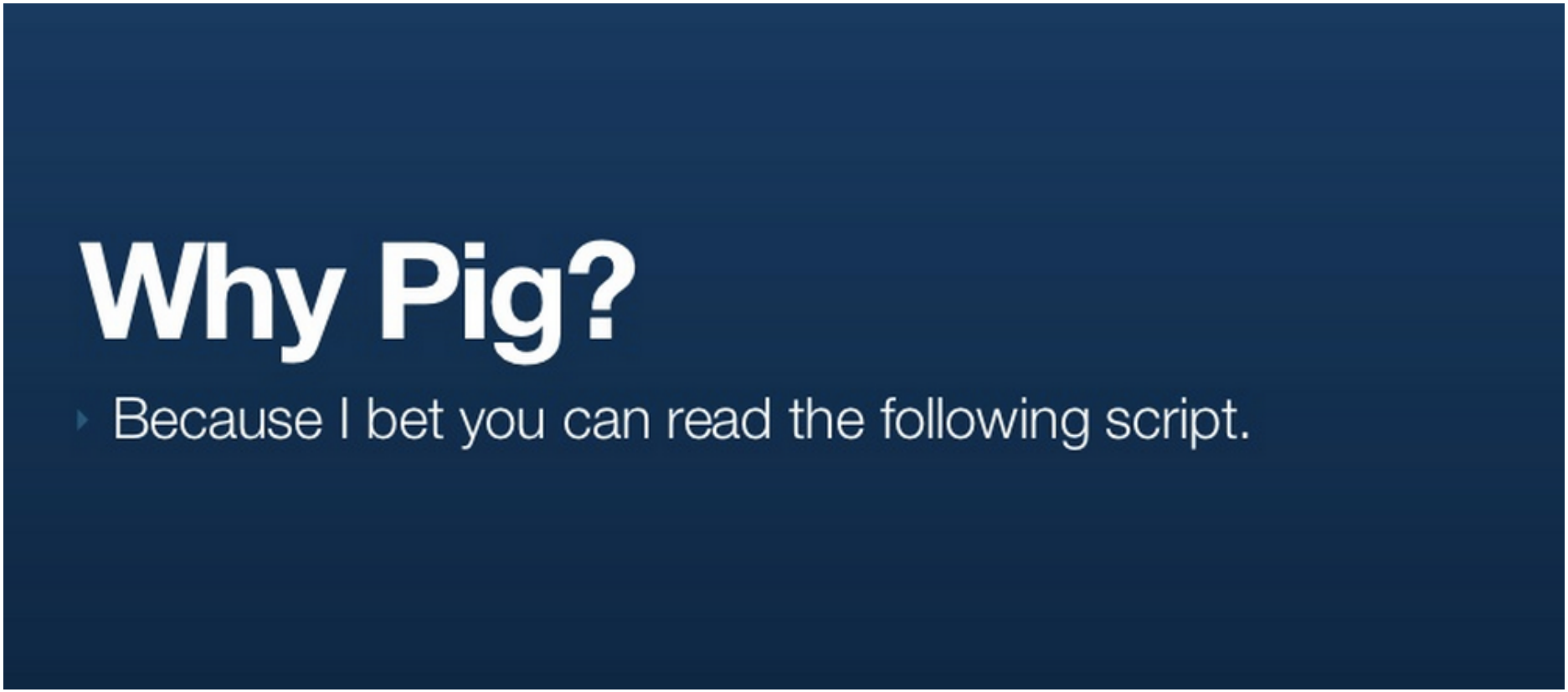
If you use Amazon EMR, you can use their file system (Amazon S3) as well.


Normal
No backup tasks
200 processes killed
Done: 839 s
Done: 1235 s
Done: 886 s
Input (MB/s)
Shuffle (MB/s)
Output (MB/s)
20000
10000
0
0 200 400 600 800 1000 1200
Seconds

It's possible to overlay the map-reduce framework with an additional declarative syntax.

This makes operations like select & join easier to implement and less error prone.

Popular examples include Pig and Hive.



source: http://www.slideshare.net/kevinweil/hadoop-pig-and-twitter-nosql-east-2009

A Real Pig Script

top_5.pig

```
users = load 'users.csv' as (username: chararray, age: int);
users_1825 = filter users by age >= 18 and age <= 25;

pages = load 'pages.csv' as (username: chararray, url: chararray);

joined = join users_1825 by username, pages by username;
grouped = group joined by url;
summed = foreach grouped generate group as url, COUNT(joined) AS views;
sorted = order summed by views desc;
top_5 = limit sorted 5;

store top_5 into 'top_5_sites.csv';
```

- Now, just for fun... the same calculation in vanilla Hadoop MapReduce.

No, seriously.

III. WORD COUNT EXAMPLE

Map-reduce processes data in terms of key-value pairs:

```
input              <k1, v1>

mapper             <k1, v1> → <k2, v2>

(partitioner)      <k2, v2> → <k2, [all k2 values]>

reducer            <k2, [all k2 values]> → <k3, v3>
```

Using the following input, we can implement the "Hello World" of map-reduce: a word count.

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```
where
where in
where in the
where in the world
where in the world is
where in the world is carmen
where in the world is carmen sandiego
```

The first processing primitive is the mapper, which filters & transforms the input data, and emits transformed key-value pairs.

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```
mapper(k1, v1):
// k1 = line number
// v1 = line contents (eg, space-delimited string)

    words = tokenize(v1)   // split string into words
    for word in words:
        emit (word, 1)
```

The mapper emits key-value pairs for each word encountered in the input data.

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```
where 1
where 1
in    1
where 1
in    1
the   1
...
```

The partitioner is internal to the map-reduce framework, so we don't have to write this ourselves. It shuffles & sorts the mapper output, and redirects all intermediate results for a given key to a single reducer.

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```
where       [1, 1, 1, 1, 1, 1, 1]
in          [1, 1, 1, 1, 1, 1]
the         [1, 1, 1, 1, 1]
world       [1, 1, 1, 1]
is          [1, 1 ,1]
carmen      [1, 1]
sandiego    [1]
```

Finally, the reducer receives all values for a given key and aggregates (in this case, sums) the results.

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```
reducer(k2, k2_vals):
// k2 = word
// k2_vals = word counts

    emit k2, sum(k2_vals)
```

Reducer output is aggregated...

```
where       7
in          6
the         5
world       4
is          3
carmen      2
sandiego    1
```

Reducer output is aggregated & sorted by key.

```
carmen      2
is          3
in          6
the         5
sandiego    1
where       7
world       4
```

NEXT STEPS

Consider yourselves officially "introduced" into the world of Data Science and machine learning.

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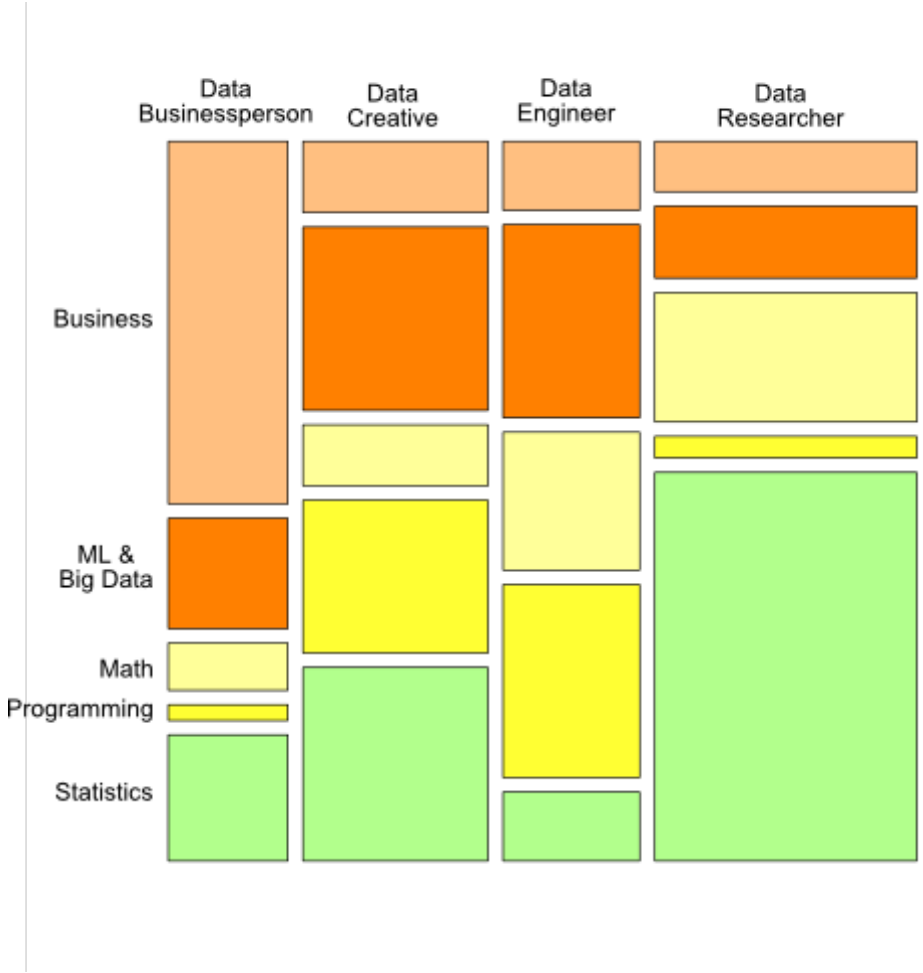
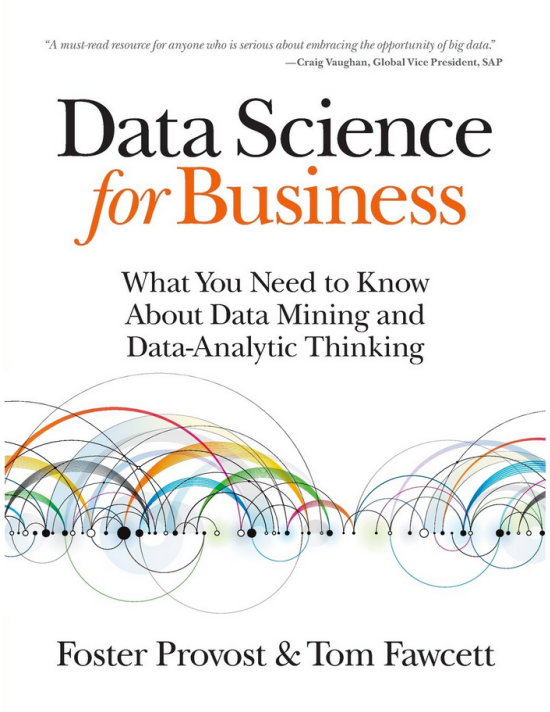
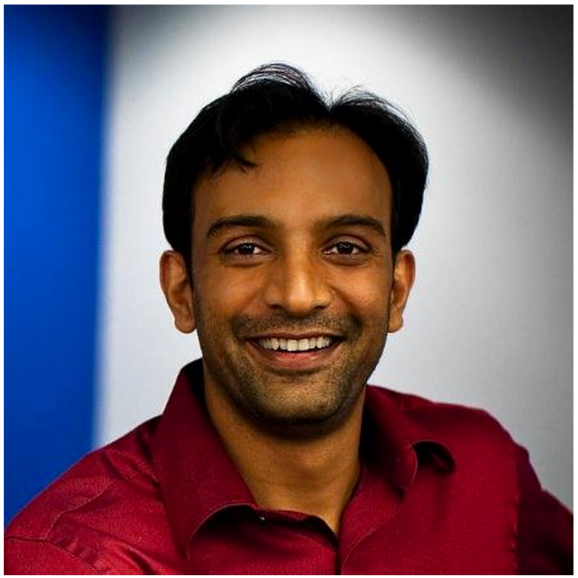
Where does one go from here?


Data Businessperson
Data Creative
Data Engineer
Data Researcher
Business
ML & Big Data
Math
Programming
Statistics

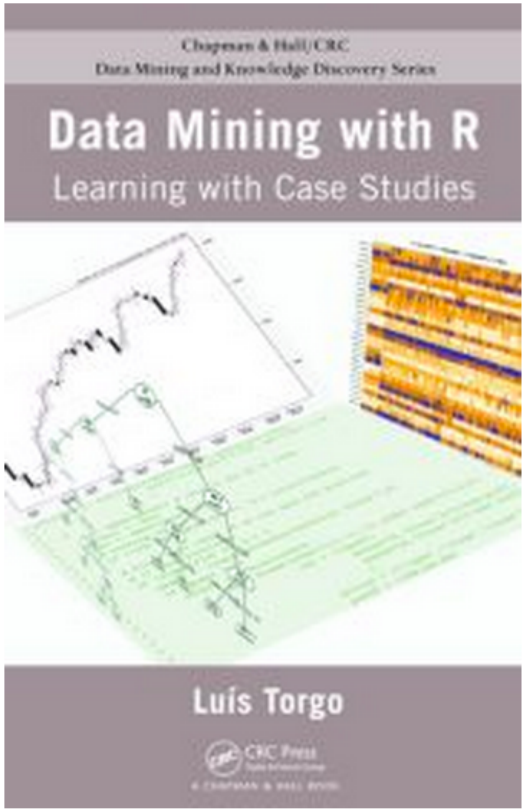
DATA "BUSINESSPERSON"

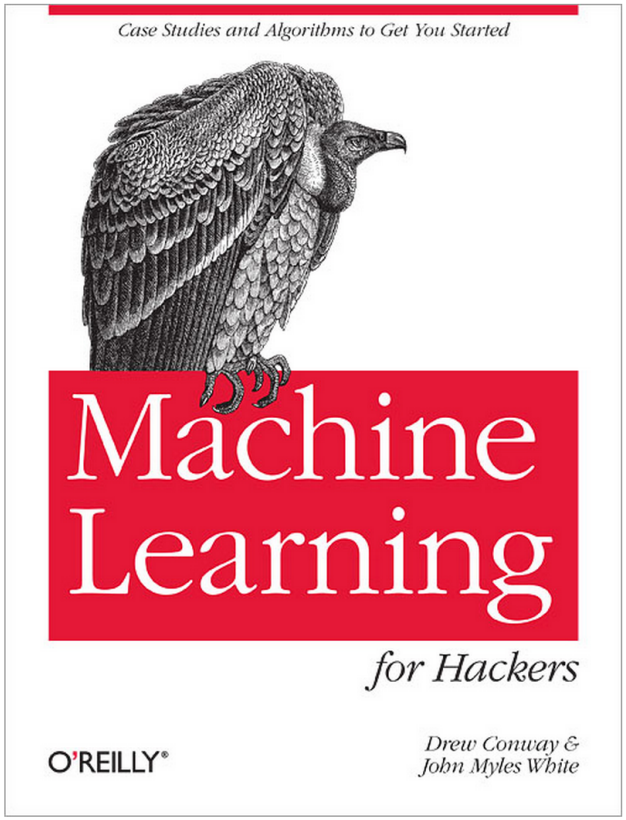
B2



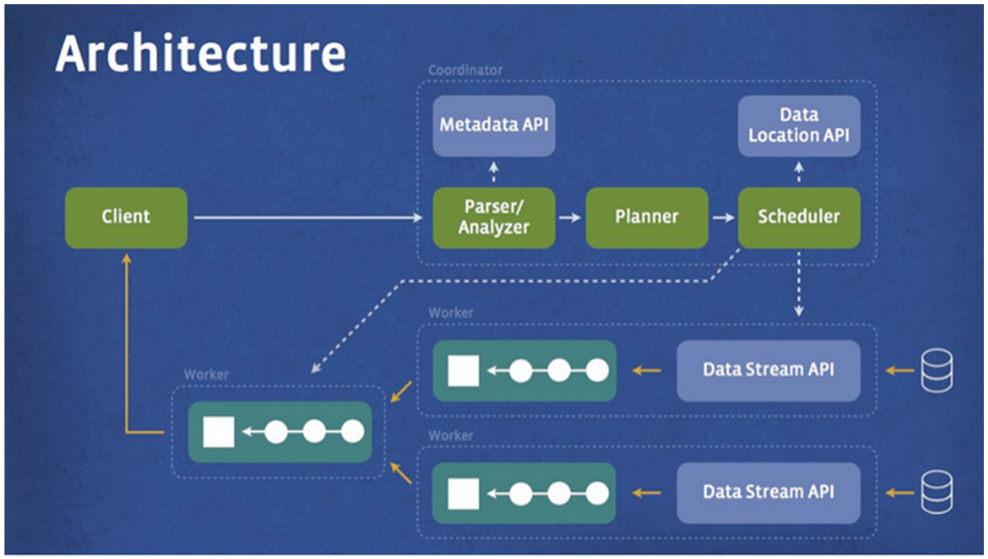


Overarching theme: do all the things.

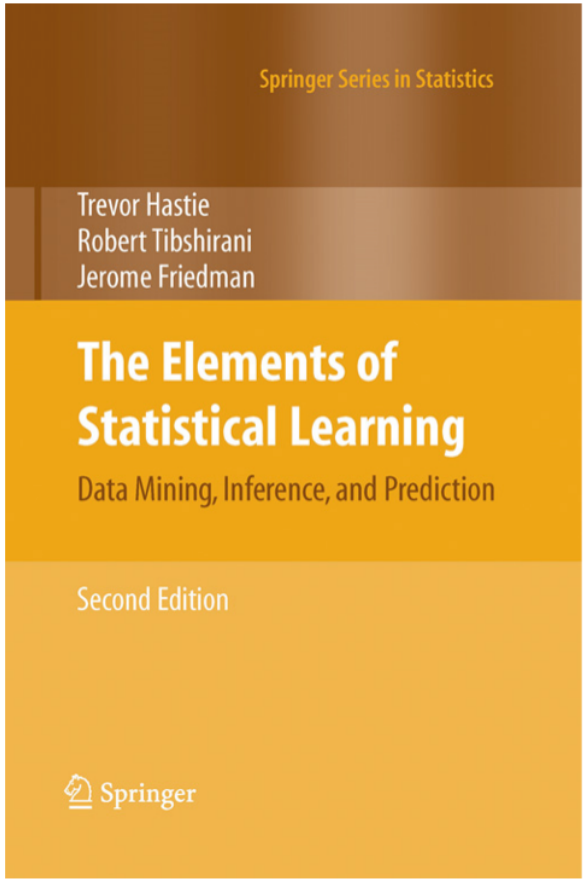




Leading question: How do you surface the data that others are looking to use for answers?



Facebook's recently announced "Presto"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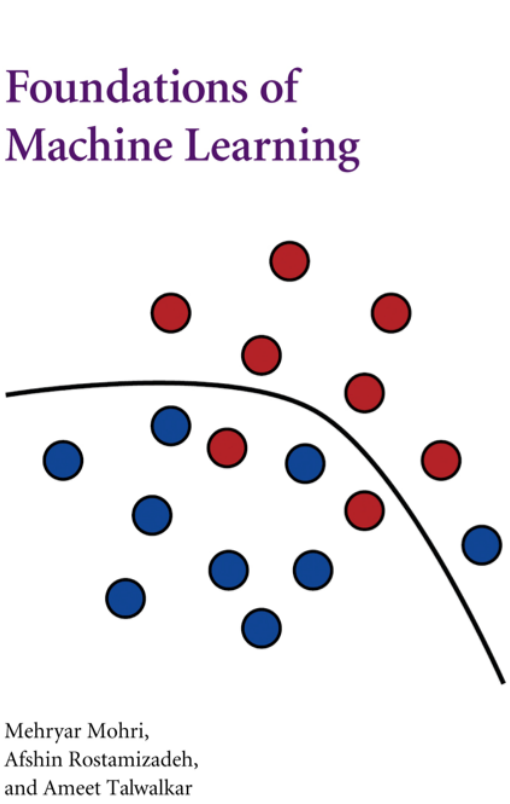
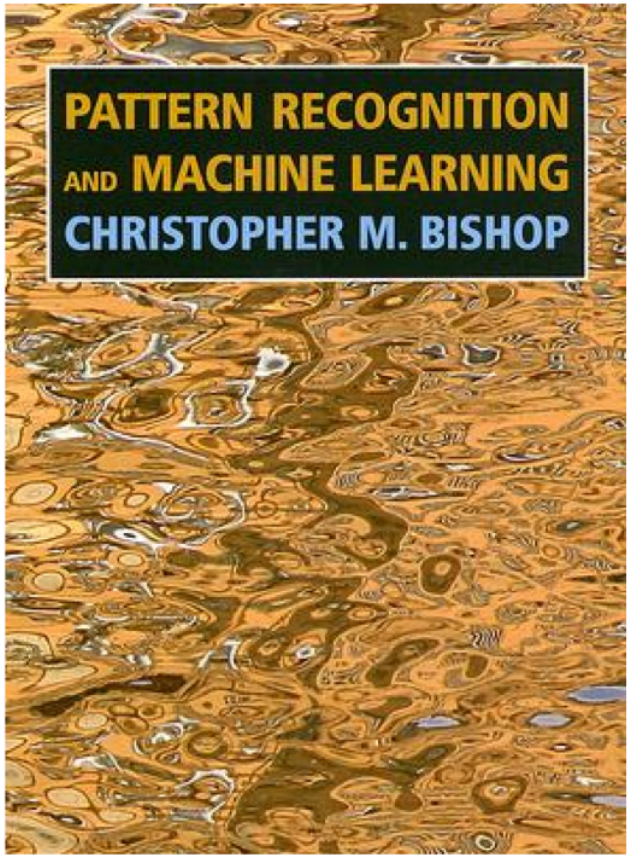

Foundations of Machine Learning
Mehryar Mohri,
Afshin Rostamizadeh,
and Ameet Talwalkar


PATTERN RECOGNITION
AND MACHINE LEARNING
CHRISTOPHER M. BISHOP

Find your niche.

Work on things.

Communicate.